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The Effect of Monetary Policy and other Macroeconomic Factors on Wealth Inequality in the United States

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Master's thesis in Economics, 30 hec

Spring 2022

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Abstract

Wealth inequality is a crescent phenomenon and topic that has been gaining attention of late, not least in the United States, but in many other countries as well. This Master's thesis seeks to discern what factors have been conducive to this increase, chiefly focusing on the role played by the central bank via setting the federal funds rate and its effect on the top 1 percentile's wealth share. To account for endogeneity between the variables we elected a Vector error correction model and additionally a VAR model, where the former also accounts for long run relationships in the case of cointegration.

A decrease in the federal funds rate was found to be associated with an increase in the top 1 percentile's wealth share in the long run. Likewise, in the long run an increase in the S&P 500 was associated with an increase in the top 1 percentile's wealth share. The short run dynamics were fairly similar; the results obtained from the impulse response functions pertaining to the VAR model indicated a positive temporary response from the top 1 percentile's wealth share subjected to a shock to the S&P 500, whereas inflation produced a transitory negative response. The results are in line with much of previous literature, though there is no absolute consensus as to all the results in the field at present.

Acknowledgement

We wish to express our gratitude to our supervisor Kristian Bolin as well as extend a special thanks to Kerstin Westergren for her valuable feedback, without which this thesis would not have been possible.

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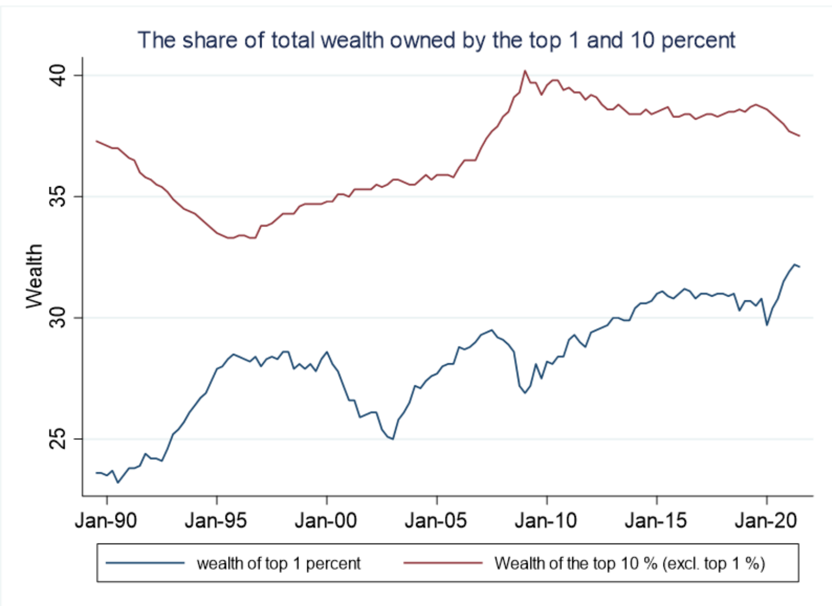
1. Introduction

Wealth inequality has increased in countries around the globe over the past decades. Saez and Zuckman (2016) highlight the development of wealth distribution since 1948. The paper presented an increase of approximately 15 % in wealth owned by the top 0.1 % of the population since 1978. The increase, coupled with low interest rates, has spurred a discussion on the causes of the development and the role of the central banks. Previous research has sought to assess the relationship by exploring the various channels through which monetary policy affects wealth and income inequality. This thesis seeks to ascertain what macroeconomic factors have contributed to this increase in wealth inequality, chiefly focusing on the federal funds rate's effect on wealth inequality through its channels of effect. Additionally, this thesis incorporates an innovation channel as a proxy for technology, which has not been extensively investigated in the field. Specifically, this thesis aims to address the question: *Does the federal funds rate have an impact on wealth inequality?*

By utilizing the most recent data on the top 1 percentile this paper confirms the development in recent years and additional increases in wealth inequality can be seen. Similar to the top 0.1 percent, the top 1 percent has increased significantly from 23,6 percent of total wealth in 1989 to 32,1 percent, as of July 2021. The further increase has spurred additional discussion on wealth inequality and the distributional effect of monetary policy.

Figure 1



The sources of economic inequality are often uncertain and continuously debated. In a recent paper, Coibion et al. (2020) separate the effects of income and wealth inequality into five different channels. The income composition channel, the portfolio channel, the income heterogeneity, savings distribution, and financial segmentation, wherein the results only presented the portfolio as having an impact. However, with the increased importance and varied results from different researchers, the relationship between monetary policy and economic inequality is continuously expanded. Additional channels, such as the effects of housing, fiscal policy (Albert et al., 2020), and the effect of technological progress (Giri et al., 2021), have been found to further explain and improve the ability to correctly apply and maintain economic policy.

In macroeconomics, not uncommonly, variables do not exhibit simple one-way causal relationships. Macroeconomic factors may rather exhibit interrelated complex relationships. E.g, a first variable may affect a second and third variable which in turn affect the first variable, not seldom occurring with delay, more akin to a feedback loop. Hence, employing models that account for such relationships is a necessity in the field. In this paper we utilize both a vector autoregressive model, using impulse response functions, as well as a vector error correction model to allow for cointegration between the factors. A similar such model that allows for cointegration was used by Davtyan (2017), also on the US population but it was focused on income inequality.

This thesis employs a dataset consisting of quarterly data between the years 1989 and 2021. Employing a VAR and a VEC model as well as including a term for technological progress, has not been adequately covered in the literature and can be considered a contribution to the macro-econometric literature on the federal funds rate and wealth inequality. It is a reasonable conjecture that from 1989 to 2021 that the ever-changing technological landscape has had some effect on the distribution of wealth in the United States. By including a term for innovation this thesis thus essays to further describe the causes of wealth inequality, and possibly what measures can be applied to limit its effect.

The following section discusses previous research in the field. This is followed by a theoretical framework for each affecting factor. The third segment describes the methods employed to estimate the effect. The fourth summarizes the results and the last segment includes a brief discussion as well as suggestions for future research.

2. Literature Review and Theoretical framework

2.1 Literature review

The research into wealth and income inequality can generally be divided into studies that aim to describe the development of wealth and income distribution over time, and studies that seek to explain the causes of economic inequality.

Different studies have been made describing several countries such as France (Piketty, 2003) and the United States (Piketty and Saez, 2003, Saez and Zucman, 2016), and some similarities can be understood from the data. In both strands of the literature, a large problem in describing wealth inequality is the difficulty in terms of measuring wealth among the population. To remedy the problem, researchers have tried different methods such as oversampling the upper part of the income brackets as well as looking at different ways of measuring wealth, e.g. a study by Saez and Zucman (2016) utilized the income tax returns as well as capitalizing on income, to measure wealth in the United States. Similar to income inequality, wealth inequality seems to follow a U-shaped pattern where their study displays a reduction in wealth inequality between 1929 to 1978, whereafter it has increased continuously. The pattern of the curve is interesting as it draws similarities to the inverted U-shape of income inequality proposed by Kuznets in 1955. In a recent article Kwon (2016) reemphasized the curve and briefly explained the original theory of the Kuznets inverted U-shape, according to which income inequality should increase with industrialization but decrease as a larger part of the labor force joins the sectors which display greater productivity. Apart from the continuous growth in wealth inequality, the US economy and its policy have seen various shocks and changes in the years since 1978. Changes such as the new policy of transparency in 1994 (Hayford and Malliaris, 2011) and various economic shocks, not least the great depression of 2007 to 2009 (Hayford and Malliaris, 2011).

The causes of changes in equality are generally divided into different channels (Albert et al. 2020, Furceri et al. 2017, Coibion et al. 2017) where each channel influences wealth or income inequality differently. Specifically, the effect of monetary policy can be divided into direct and indirect effects, where direct effects are immediate effects caused by a change in monetary policy, such as the effect of interest rates on loans. Indirect effects can instead be caused by a change in the market equilibrium, which comes as a result of monetary policy. Examples of the latter are changes in output and demand indirectly affected by monetary policy (Ampudia et al. 2018). Lastly, monetary policy is itself a broad term for several tools that can be used by a government to affect the local and the global economy. Often discussed tools used by the federal reserve are *open market operations* and the *discount window* and the *discount rate* (*fed.gov*).

As previously mentioned Coibion et al. (2017) introduced five channels that are connected to monetary policy. The income composition channel, the financial segmentation channel, the portfolio channel, the savings distribution channel, and the earning heterogeneity channel. Albert et al. (2019) further extended the discussion by also including the housing channel as well as the fiscal channel. These channels are not necessarily the only affecting channels and researchers are continuously working on understanding the relationship between monetary policy and wealth as well as income inequality. Whereas all channels are essential in describing the causes of economic inequality (as caused by monetary policy), the discount rate is often used as the factor which reflects monetary policy decisions and their direct effects. The effect is reflected in *the savings redistribution channel,* which describes the effect on economic inequality that stems mainly from a change in policy rates or inflation. A reduction in interest rates is assumed to have a positive effect on borrowers versus a negative effect on savers, due to lesser interest payments. (Coibion et al. 2017). The latter can be further divided by looking at inflation as *the unexpected inflation channel,* which will be further described in later sections.

direct and indirect effects

The effect of monetary policy can be further divided into direct and indirect effects, as described by Kaplan et al. (2018) and discussed by Ampudia et al. (2018). Direct effects are described as having an immediate effect, such as the effect of an increase in the interest rate on a household's monthly expenditure. Furthermore, direct effects are heterogeneous across groups as households with differences in initial wealth or indebtedness will experience varied results. While the channels may both induce indirect and direct effects they can generally be divided into one of the two groups. The savings distribution channel is therefore often interpreted as having a more direct effect, compared to earning heterogeneity and income composition which are more affected through indirect effects on the market equilibrium.

Ampudia et al. (2018) summarize some of the research in the field in their recent study and note that while the effect of expansionary monetary policy can be seen to have a negative impact on inequality, they also argue that the effect is much harder to distinguish relative to wealth. Wealth inequality is believed to see similar results, however, it has proven more difficult to clearly state due to the difficulties in measuring wealth between households. While several studies have been conducted describing the various effects of monetary policy, the overall effect is still debated. Contrasted to the previous discussion, Bernanke suggests that while economic policy surely has an effect, the net effect may be either positive or negative in the long run and that while there is an effect, the main cause of inequality may adhere to deeper structural effects rather than short term government policy (Bernanke, 2015).

Theoretical modeling on optimal monetary policy

Studies investigating the effects of monetary policy can be further divided into studies that investigate the distributional powers and studies that aim to look at optimal monetary policy. A common theoretical foundation of papers that seek to optimize policy is the New Keynesian framework, which is utilized through stylized theoretical modeling, in which the researcher computes optimal levels of monetary policy which they test using an empirical framework. Bartolomeo et al. (2016) use a model that looks at the optimal level of monetary policy in a New Keynesian framework. Additionally, there are several studies that utilize similar New Keynesian models in assessing optimal levels of monetary policy for various purposes. Söderström et al. (2005) present a model using the New Keynesian framework which further investigates the optimal preference parameters for the central bank. A somewhat similar model was applied by De Waal et al. in 2017 but in the case of South Africa. Their study utilizes a global New-Keynesian DSGE model in order to determine how foreign monetary policy shocks may affect domestic policy responses. Furthermore, such models are applied assuming either representative or heterogeneous agents. More recently papers have begun adopting heterogeneous agent models with incomplete markets. If a study is focused on income and wealth inequality a heterogenous model would intuitively be better since both income and wealth are different between individuals and households (Colciago et al., 2019). Nevertheless, the argument could still be made that representative agent models are sufficient to analyze the effect of policy decisions concerning the macroeconomy. The base of the argumentation comes from a study by Krusell and Smith (1998) in which they argue for limited effects on the macroeconomy from heterogeneity between households.

Therefore, in essence, a representative agent model could reflect the true relationship as closely as a heterogeneous agent model.

Inequality and innovation

The discussion on inequality and technological progress has been further emphasized in recent years. The relationship which was famously argued by Kuznets in 1955 has since been studied with varying intensity.

Piketty's framework suggests there to be a race between technology and education, giving rise to income inequalities. The race refers to the fact that many jobs, especially manual non-intellectual jobs, increasingly are being automated and thus disappear. There is therefore a decline in those manual non-intellectual jobs, whereas there has been an increase over the last 30 years in jobs heavier on the intellectual and/or ingenuity side, typically requiring high educational attainments. Moreover, technological advancements tend to increase productivity in the more intellectual types of jobs, where this productivity increase accrues to capital owners and high earners. The widening between technology and education refers, further, to the supply and demand side. If education does not increase enough, supply is low, and the increase in demand for high-skill labor gives the highly educated and skilled increased wages, especially given high bargaining power. The obverse is rather the case for the lower skill, manual work, requiring less education, where there have been declines in demand and wages. Piketty, however, did not find this explanation sufficient for the staggering increase in the top 1 percent's income inequality. Hence, he further suggests that there are other factors at play. These include policies such as sizable decreases in top marginal income tax rate, low bargaining power in hierarchical orderings of companies, and sentiments and norms as to the importance and influence of top managers on how a company fares economically. Piketty thus suggests that the staggering increases for the top earners were not attributable to dramatic productivity increases, but rather such factors described above and e.g., that marginal tax rate decreases rather made rent seeking-behavior, such as for managers to seize a larger share of the income in companies instead of distributing among workers and shareholders, more profitable and appealing. Other factors that Piketty does not account for is for instance that technology has enabled globalization. Globalization has created a much larger market with considerable competition within the tradable sector, thus engendering a shift in labor in the US towards the non-tradable market where there is no competition from the whole world competing with wages and skills. 'Tradable' goods and services are thus subject to such large competition on the global market whereas 'non-tradable' goods and services (things that are not as easily outsourced or offshored such as healthcare) are not. In the tradable sector big players can get considerable global market power, as well as renowned top skilled workers, and can then make extreme profits as there appears to be a sizable type of barrier to entry to qualify as either of those. The result of these forces is increased income inequality as well as wealth inequality especially as there is no perfect market in this arena, due to the market power these players hold. The policies implemented in the United States have rather facilitated all of these effects rather than have sought to cushion their impact. (Boushey, Delong and Steinbaum, 2017)

The 5 channels of effect

The savings redistribution channel

In the previous section the *savings distribution channel* was briefly described, suggested by Colciago et al. (2020) as a channel encompassing both the effect of inflation as well as the effect of interest rates. This channel can be further divided by removing the *unexpected inflation channel* and investigating them separately, as is done in this thesis. The savings distribution channel is meant to capture the effect of a change in interest rates. As previously mentioned this implies that a positive change in the interest rate will lead to a benefit for savers but a loss for borrowers (Colciago et al. 2019). By assuming that lower bracket households will be more likely to be borrowers rather than savers this is conducive to an increase in inequality.

Furthermore, the effect of the discount rate is well documented in economic theory and can be suggested to share a relationship with plenty of other macroeconomic factors. Often discussed is the interest rates' negative effect on investments (partly through its effect on the cost of capital), inflation, and possibly economic growth (through a reduction in investments). Additionally, as the interest rate affects inflation it can also be argued to affect unemployment through the classic Phillips curve (Olsson, 2012).

The unexpected inflation channel has a similar effect as the savings redistribution channel and in general, affects the older and richer households worse in comparison to less wealthy and younger households, as these are more likely to be savers rather than borrowers (Doepke and Schneider, 2006). This is somewhat different from another study by Erosa and Ventura

(2002), which indicated that because of the larger proportion of cash held by poorer households, these households would be more severely affected by increased inflation. The effect of inflation has further been tested by previous studies, which describe the relationship between inflation and economic inequality through its relationship with economic growth as well as through wage versus asset income (Zheng et al. 2020). Recent studies (Zheng. 2020, Zheng et al. 2020) have presented similar mitigating effects of inflation on income inequality, as shown by Doepke and Schneider (2006), mainly through its effect on the interest rate and decreased economic growth. Additionally, a study by Menna and Tirelli (2017) showed that a lower tax combined with greater inflation may decrease economic inequality. Similar results have been found in developing countries where a greater degree of inflation may decrease economic growth but also reduce income inequality. The relationship is, however, non-linear and may adhere closer to an inverted U shape in which increased growth may reduce income inequality in the long run (Siami-Namini and Hudson, 2019). Whereas the effect of inflation is constantly debated, Colciago et al. (2019) in their summarizing study suggest that the overall effect of inflation is believed to promote inequality.

The earnings heterogeneity channel reflects the differences between types of employment between households. Therefore, households that are dependent on less stable jobs are more greatly affected by a reductive monetary policy (Coibion et al., 2017). Additionally, households in the lower wealth and income bracket tend to be more affected by these channels as they generally have a greater part of their income from less stable jobs as well as are more likely compared to higher income brackets to be unemployed. In a study by Carpenter and Rogers (2004), they displayed the disproportionate effect that monetary policy has on especially minority groups, teenagers, and out-of-school men and women.

Not seldom is the income composition channel investigated together with the earnings heterogeneity channel (Bárcena-Martin et al. 2019). The income composition channel reflects the differences between households' relative types of income. Households with a greater degree of income from labor relative to businesses or financial capital may face different difficulties when pressured by a specific monetary policy change (Coibion et al. 2017). The *earnings heterogeneity channel* compared with the *income composition channel* reflects differences in types of employment rather than types of income. Due to the characteristics of these channels, they are often represented through studies that utilize survey data, sometimes on one or two countries, as in Park (2021), and sometimes on multiple countries as in a study by Bárcena-Martin et al. (2019). The *heterogenous earnings channel* may be especially important for income inequality as shown by Park in a recent study from 2021. However, the study also described the effects as limited in power and may present limited issues compared to more important factors such as systems of education, welfare, and tax.

The portfolio channel reflects the differences in accumulated financial assets between households, where the underlying theory suggests that if a household is in the upper bracket they will have been able to accumulate a greater amount of financial assets and will therefore gain more from a positive change to the market. The channel is often compared with the *financial segmentation channel* which reflects the effect of financial trading and the relative difference in accessibility between low-income and high-income households. The assumption is that households that partake in trading to a greater degree would receive larger benefits from an expansionary monetary policy, which in turn would benefit the upper wealth brackets to a larger extent (Coibion et al. 2017). Two recent papers by Albert et al. (2020) and Alves and Thomás (2021), further looked at the channels of effect which may affect both wealth and income inequality. While the two were conducted slightly differently both showed a positive response to wealth inequality adhering to the portfolio channel. Additionally, the two studies looked at separate areas, whereas Albert et al. (2020) investigated the relationship in the USA, Alves and Thomás (2021) further investigated the relationship in the Eurozone countries.

The relationship between innovation, economic growth, and inequality

Laura Tyson and Michael Spence expound on wealth inequality and income inequality, expanding and commenting on previous seminal works such as that of Piketty, largely from a technological point of view as they consider technology to play a pivotal role in wealth and income inequality. Not only is technology an important explanatory factor for inequality but it also contributes to growth in the economy by way of e.g., improving productivity. There are also various complementary explanations for the rise in wealth and income inequality and Laura Tyson and Michael Spence do not explicitly distinguish between factors affecting wealth inequality from income inequality as there is a connection between the two. (Boushey, Delong and Steinbaum, 2017). Piketty is considerably more specific on that front, ascribing much of the arisen income inequality to a “race between technology and education” and that wealth inequality rather is explained by the gap between r and g, where r denotes the rate of return from capital and g is the growth of the economy. (Boushey, Delong and Steinbaum, 2017, p.177). Piketty avails himself of a familiar production function with capital, technology, and labor, where there are diminishing returns. Although the capital stock has continuously increased over the years, thereby incurring diminishing returns, there has still been an unwavering increase in capital stock as the diminishing return effect has been counteracted by increases in technology that help and enhance capital return. The argument is that capital return (r) usually is larger than the growth rate of the economy (g) and that capital tends to be owned by relatively few (or at least capital tends to not be equally distributed in a population) thus capital gain accrues unequally to the population which results in wealth and income inequalities. (Boushey, Delong and Steinbaum, 2017)

2.2 Theoretical framework

The focus of this thesis is to understand the distributional effects of monetary policy and not to evaluate optimal monetary policy. A brief discussion was included to appreciate that a large part of the field applies various other types of models. This thesis is rather to rely on a theoretical framework based on previous research and theory regarding the relationships between monetary policy and macroeconomic factors. In later sections variables are to be tested, aiming to represent the effects that are discussed in this section. The thesis includes three channels to be assayed, the savings distribution channel (divided into the savings redistribution channel and the unexpected inflation channel), the earning heterogeneity channel, as well as the portfolio channel. In addition, the effect of real GDP, unemployment, and innovation are included. The following section will emphasize the relationship between the variables as well as include previous research that documents the relationship between the variables and inequality. The latter is meant to define the expected relationship with inequality by using previous research.

2.2.1 The effects of macroeconomic factors on economic inequality

The first channel represented is the *unexpected inflation channel*. Several researchers have investigated its effect and as expressed by Colciago et al. (2019) the general consensus is that inflation tends to increase inequality. There are, however, papers that have produced different results such as Siami-Namini and Hudson (2019) as well as an important paper produced by Doepke and Schneider in 2006, which enforces the ambiguous nature of the variable. In essence, an increase in inflation is believed to reduce wealth inequality but there are mitigating factors that may lessen the effect on inflation. Secondly, the *savings distribution channel,* as expressed through the federal funds rate is applied to both represent the intervention of the state and also the effect of an increase in the discount rate on wealth inequality.

The third channel, the portfolio channel is represented through changes in the S&P500 (Standard & Poor's 500), the prominent large-cap index covering 500 heavily traded American stocks. The variable was previously used in a similar way, representing the portfolio channel, in a study by Albert et al. (2020). The conjecture would be that a positive change in S&P 500 will be conducive to a positive effect on wealth inequality, represented through the wealth owned by the 1 and top 10 percent. Several other papers have discussed the portfolio channel including a well-known previously cited article by Coibion et al. (2020).

The fourth channel that the paper hopes to represent is the earnings heterogeneity channel, for which the argument is that households that have less stable jobs are more harshly affected by a reductive monetary policy, and as these households tend to be in lower wealth brackets, this would be conducive to an increase in inequality (Coibion et al. 2017). The variable is thus believed to have a positive relationship with wealth inequality.

Lastly, the inclusions of innovation as well as real GDP. One of the reasons for the inclusion of the real GDP was that it was considered likely for there to exist a relationship between real GDP and economic inequality. The belief was further enforced by previous studies by Siami-Namini and Hudson (2019) and Zheng et al. (2020) that have further expressed the relationship between economic growth and economic inequality and its close connection to inflation. Similar to the market index, an increase in economic growth is expected to induce an increase in inequality rather than a decrease.

3. Methodology

3.1 Data

The data employed in this thesis was chiefly obtained from the Federal Reserve Bank of St Luis. Other sources include investing.com, the United States Patent and Trademark Office, and The Federal Reserve. The data consists of quarterly observations between 1989 and 2021 in the US. The data contains of the following: *the share of total wealth owned by the top 1* *percentile as well as the 90 to 99 percentile (the main dependent variable in the study), inflation (consumer price index), S&P500 (A market index over the top 500 businesses in the US), Real GDP, The federal funds rate, innovation (number of utility patents) and unemployment.* For the purpose of interpreting the results, all variables which are not in percentage form are transformed into their logged forms, so as to allow for interpretations of elasticities.

The variables applied in this study are aimed at looking at the various effects suggested by previous research. In their paper, Coibion et al. (2017) introduce 5 channels in which monetary policy is hypothesized to affect wealth and income inequality. As the main focus of this paper is wealth inequality and the data is macro data the thesis cannot test all channels. The paper will aim to test the *unexpected inflation channel*, *the savings redistribution channel, the portfolio channel, and the heterogenous earnings channel.* Furthermore, real GDP is added as well as a channel of innovation, which is meant to investigate the relationship between innovation and wealth inequality.

The main explanatory variable is the total wealth share, which is represented through both the top 1 percent but also the top 90 to 99 percentiles. The separation is made to emphasize the distinction between the two groups and how they may be affected differently by changes in the channels of effect. The underlying assumption is that an increase in the share of total wealth will indicate a further concentration of wealth and therefore increase wealth inequality. The share of total wealth has previously been represented by Albert et al. (2020), who utilized the log of top 1 percent wealth in a similar study looking into the effects of income and wealth inequality. The remaining variables are meant to capture the effects described in previous research. As can be observed in the figure in the appendix (figure A.2) showing the wealth variables, both the percentile groups have seen increases since 1989 however only the top 1 percentile has significantly increased while the top 90-99 percentile group has seen both increase and decline, ultimately ending around a similar percentage as in 1989. The following table describes the constitution and form of the data and summarizes the variables tested in the models. For a more extensive description of the collection and construction of the variables see, the appendix (variables and graphical illustrations).

Table 1 - *Descriptive statistics*

Variables	*Observations*	*Median*	*Mean*	*Min*	*Max.*	*Std.deviation*
Top 1 percentile's wealth share	*129*	*.283*	*.2817364*	*.232*	*.322*	*.0224268*
Top 10 percentile's wealth share	*129*	*.368*	*.3673178*	*.333*	*.402*	*.0196787*
Federal Funds Rate	*129*	*.024*	*.029169*	*.0004*	*.0924*	*.0256459*
log(Real GDP)	*129*	*9.612887*	*9.543529*	*9.131818*	*9.877087*	*.2248954*
log(CPI)	*129*	*5.059044*	*5.03594*	*4.60517*	*5.391115*	*.2143526*
log(S&P 500)	*129*	*7.110206*	*7.045074*	*5.723912*	*8.368122*	*.6407086*
log(Innovation)	*129*	*9.881293*	*10.10785*	*9.026177*	*11.48304*	*.7448101*
Unemployment	*129*	*.054*	*.0585504*	*.033*	*.112*	*.0165888*

3.2 The Methodological Process

The paper will utilize the four-step Engle-Granger methodology as discussed by Enders (1995) to investigate the research question at hand, thus determining whether the variables share a long-run stochastic trend and whether they have an impact on wealth inequality. The four steps comprise: unit root testing and cointegration testing thereby determining the order of integration, estimating the long-run relationship, determining the vector error correction model, and lastly, interpreting the model and running concluding diagnostics. The presence or absence of a long run relationship, as determined in the four steps procedure, is essential for the choice of model and which dynamics can be investigated.

The VAR and the VECM framework were elected as the models for the calculations to be performed. The models are particularly useful since they account for endogeneity, allowing for cross-relationships over the variables (Gujarati and Porter, 2009). The vector error correction model is used for the purpose of investigating the presence of a long-run relationship between the variables and wealth inequality. The assumption would be that the variables utilized in our method would experience a long-run stochastic trend which would bring them closer over time. If two or more variables are cointegrated they will not be stationary in their leveled forms. This is often the case with macro-level data, as is understood when analyzing the development over time.

4. Results section

4.1 Stationarity and testing for Unit Roots

The first step concerns stationarity and the determination of unit roots within the sample. This is of import since cointegration requires the variables to be integrated of the same order (Enders, 1995). The simplest and most intuitive way of discovering whether a variable is experiencing a trend is by plotting the variable over time. In returning briefly to the description of the variables this can be confirmed as the case for most if not all of the variables utilized in this study. A trend can be categorized as a deterministic trend, i.e., a nonrandom trend over time, or a stochastic trend that is random over time (also called a random walk). Furthermore, the distinction between a stochastic and a deterministic trend can be made using Unit-Roots. If the variable can be tested to have a unit root, the variable can be said to have a stochastic trend and therefore also be non-stationary. Testing for a unit root is often done using a Dicky-Fuller test. The test can be expressed with the following equation:

$$\Delta Y_t = \beta_0 + \delta Y_{t-1} + u_t \tag{4.1}$$

for which the null hypothesis is that there is a unit root, and the one-sided alternative is that the variable is stationary. The δ is called the Dickey-Fuller statistic and is computed using homoskedasticity only standard errors. Furthermore, the model can be extended to include more lags as well as control for other trends. The extension is called the Augmented Dicky-Fuller test (ADF) and can be extended to include p number of lags. The results of the tests are then compared with their corresponding critical values. As the DF statistic is not normally distributed the critical values can only be compared with a certain set of critical values. The statistic will also tend toward negative values reflecting a one-sided result. (Stock and Watson, 2015).

The test is computed in two steps. The first step determines the stationarity or the Unit Roots of the variables in levels i.e. the variables are taken as they are which is in contrast to taking the first difference which soon is to be shown as well. The variables are expected to be non-stationary when dealing with macroeconomic data. The model's number of lags is determined through testing from our own data and previous research. Furthermore, Enders (1995) notes that when using quarterly data, using lags that have multiples of 4 is natural. Mainly from testing but also from previous documentation on lag length, 8 lags were deemed the most preferable. Whereas the test can be conducted with various lag lengths to assess sensitivity and options to incorporate trends, the most relevant ones are presented in table 2 below with 8 lags and with the intercept specification accounting for a drift. The models did not exhibit sensitivity to lag length and to achieve stationarity first difference will be employed which can be observed in table 3 instead. As can be observed from table 2 none of the variables, save for unemployment, are stationary in levels.

Table 2 - *Augmented dicky fuller test with variables in level and 8 lags and intercept.*

		Critical Values			
Variables	*T-statistic*	*1%*	*5%*	*10%*	*P-Values*
Top 1 percentile's wealth share	*-1.456*	*-3.504*	*-2.889*	*-2.579*	*0.5553*
Top 10 percentile's wealth share	*-1.707*	*-3.504*	*-2.889*	*-2.579*	*0.4277*
Federal Funds Rate	*-1.466*	*-3.504*	*-2.889*	*-2.579*	*0.5501*
log(Real GDP)	*-2.462*	*-3.504*	*-2.889*	*-2.579*	*0.1250*
log(CPI)	*-1.227*	*-3.504*	*-2.889*	*-2.579*	*0.6619*
log(S&P 500)	*-0.368*	*-3.504*	*-2.889*	*-2.579*	*0.9153*
Innovation	*-0.208*	*-3.504*	*-2.889*	*-2.579*	*0.9376*
Unemployment	*-2.937*	*-3.504*	*-2.889*	*-2.579*	*0.0412**

The second step of testing Unit Roots entails testing the variables in their first difference form, thus the variables are also thereby rendered into their percentage change form. If a variable is found to contain a Unit Root in its leveled form but not in its first difference the variable can be said to be I(1), i.e., integrated of order 1. As can be seen from the following table almost all the variables can be said to be I(1), as they are non-stationary at levels but stationary in their first difference. The exception to this was unemployment which turned out stationary even in its leveled form. Additionally, the top 90 to 99 percentile wealth bracket was only stationary at 10 percent.

Table 3 - *Augmented Dicky Fuller test with variables in first difference and 8 lags.*

Variables	*T-statistic*	*Critical Values*			*P-Values*
		1%	*5%*	*10%*	
Top 1 percentile's wealth share	*-3.207*	*-3.504*	*-2.889*	*-2.579*	*0.0196**
Top 10 percentile's wealth share	*-2.819*	*-3.503*	*-2.889*	*-2.579*	*0.0556*
Federal Funds Rate	*-3.511*	*-3.504*	*-2.889*	*-2.579*	*0.0077**
Real GDP	*-2.865*	*-3.501*	*-2.888*	*-2.578*	*0.0496**
CPI	*-3.661*	*-3.501*	*-2.888*	*-2.578*	*0.0047**
S&P 500	*-3.181*	*-3.501*	*-2.888*	*-2.578*	*0.0211**
Innovation	*-3.962*	*-3.501*	*-2.888*	*-2.578*	*0.0016**
Unemployment	*-3.751*	*-3.501*	*-2.888*	*-2.578*	*0.0035**

4.2 Testing for cointegration

In assessing whether a set of variables are cointegrated one must either use economic theory, graph the data, or perform statistical tests (Stock and Watson, 2015). Graphs (or figures) describing the variables over time can be found in the appendix under the variables section. Whereas all variables seem non-stationary in their leveled forms, it is unclear whether they share a common stochastic trend.

As previously mentioned, in order for two variables to be cointegrated they must share a long-term stochastic trend. The error correction term $(Y_{t-1} - \Omega X_{t-1})$ must, therefore, be stationary, while the variables are nonstationary. How the test is modeled depends on the knowledge of the cointegration term (Ω). When the cointegration term is known the augmented dicky fuller test can be conducted to confirm whether the error correction term has a unit root. If the test rejects the hypothesis that there is a unit root, the paper can continue using the vector error correction model (Stock and Watson, 2015). In order to test for cointegration, a valid method is the Johansen test for cointegration (Johansen, 1995) or the Engle-Granger test, for which the latter is used for the purpose of this paper.

The Engle-Granger test is a test in two stages where at first we run a long-term regression from which we then collect the residuals and investigate whether the residuals have a unit root. If the linear combination does not display stationarity in its residuals the variables do not share a long-run trend. The Eagle-Granger test can be written as follows:

$$Top1wealth\ share = \alpha_0 + \Sigma_{i=1}^{n} \alpha_i x_i + \varepsilon_i \quad (4.2)$$

where α_0 represents the intercept, α_i, the variable vector and ε_i which represents the error term. The residuals of the long-run regressions are collected and the Dicky-fuller test is run to check for a unit root. The test is run both for the top 1 and top 10 percent as well as different combinations of parameters.

From the testing phase, it was found that but a few variables displayed a cointegration relationship. The most fundamental results are summarized in the table below. Whereas the top 90 to 99 percentile bracket did not display clear signs of cointegration with several of the other variables, the top 1 percent displayed at a 5 % significance level a cointegrated relationship with both the federal fund rate and as well as the S&P500 market index. While the test proved significant, Stock and Watson (2015) note the importance of reinforcing cointegration beliefs with institutional knowledge and economic theory as cointegration testing has a risk of rejecting the null hypothesis of no cointegration more often than preferable. The relationship between both monetary policy and the market with wealth is greatly discussed in the field (as previously mentioned), whereas some researchers have specifically noted the importance of the market on wealth concentration (Ablert et al. 2020). As both the testing as well as the previous research indicate a strong relationship between the three variables, this thesis will continue with a vector error correction model to test the impact of each variable on wealth inequality. Since the top 90 to 99 percentile did not indicate the same relationship to be cointegrated, the thesis will follow only using the top 1 percentile as a dependent variable.

Table 4 - *Engle-Granger cointegration test*

Combination of Variables	*test statistic*	*1 % critical value*	*5 % critical value*	*10 % critical value*
top 1 % Wealth share, federal funds rate, the S&P500	*-3.843*	*-4.409*	*-3.808*	*-3.501*

4.3 The VECM - A long run analysis

The second step of the Engle Granger methodology as described by Enders, (1995) is to estimate the long run equation of the VECM which can be performed simply by estimating OLS for the cointegrated variables in the VEC framework.

Table 5 - *The long-run equation*

Top 1 percentile Wealth share	*Coefficient*	*Std. err.*	*P-value*
Federal Funds Rate	*-.4063459*	*.1323093*	*0.002*
S&P500	*.0152268*	*.0059403*	*0.010*
Constant	*.2389484*		

The long run relationship equation, which can be deduced from the table, turned out thus:

$$Top1ws_t = 0.2389484 - 0.4063459FFR + 0.0152268S\&P500 \quad (4.3)$$

As can be observed from the table above, the Top 1 percentile's Wealth share is negatively associated with an increase in the Federal Funds Rate in the long run. Or stated differently, a decrease in the federal funds rate appears to be conducive to wealth inequality in the long run. Similarly, an increase in the S&P 500-index is associated with an increase in wealth inequality. Both of the variables were highly significant at the 5% level. Although one should be very cautious in terms of interpreting or over interpreting the coefficients, a 1 percentage point decrease in the federal funds rate is associated with a 0.4 percentage point increase in the Top 1 percentile's Wealth share over the long run.

Having established stationarity and the presence of cointegration, the third step of the Engle Granger methodology is to estimate the VEC model in its entirety. Following Enders (1995), the VEC model is an extension of the VAR model and generally can be expressed thus:

(4.4)

$$\Delta y_{1,t} = \mu_1 + \sum_{i}^{p} \theta_{11i} \Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{12i} \Delta y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{1ki} \Delta y_{k,t-i} + \delta_1 ECT_{t-1} + \varepsilon_{1t}$$

$$\Delta y_{2,t} = \mu_2 + \sum_{i=1}^{p} \theta_{21i} \Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{22i} \Delta y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{2ki} \Delta y_{k,t-i} + \delta_2 ECT_{t-1} + \varepsilon_{2t} \quad .$$

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$$\Delta y_{k,t} = \mu_k + \sum_{i=1}^{p} \theta_{k1i}\Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{k2i}\Delta y_{2,t-i} ... + \sum_{i=1}^{p} \theta_{kki}\Delta y_{k,t-i} + \delta_k ECT_{t-1} + \varepsilon_{kt}$$

in which there is a k number of linear equations with p order of lags, the y_i terms denote the dependent variables in the system, t denotes time of a variable, the θ terms are just coefficients to be estimated, the δ terms denote the speed of adjustment, and the ECT_{t-1} denotes the Error Correction Term. The specifics as to the VEC model and its estimation can be found in the appendix, as this segment is mainly devoted to the results and their interpretation.

The δ term, as mentioned above, denotes the speed of adjustment i.e., the speed at which the short run model(s) return(s) towards the long run equilibrium. It should be between 0 and -1 for there to be such a return and not greater in magnitude as that would imply a return beyond the long-run equilibrium (Enders, 1995).

For the top 1 percentile's wealth share, the federal funds rate and the S&P 500 partial equations the error correction terms can be found in the table below, respectively, where they are denoted δ_1, δ_2 and δ_3.

Table 6 - *Table of the Error Correction Terms*

Variable	*Coefficient*	*Std. err.*	*z-value*	*P-value*
δ_1	*-.1281745*	*.0411308*	*-3.12*	*0.002*
δ_2	*-.0661699*	*.0679616*	*-0.97*	*0.330*
δ_3	*-.2890836*	*.9393654*	*-0.31*	*0.758*

Although all coefficients had the expected negative sign, indicating an adjustment towards the long run equilibrium, only the δ_1 i.e. the coefficient for the top 1 percentile's wealth share equation part was found significant. It assumed the value -0.1281745 indicating a return towards the long-run equilibrium at a speed of 12.8% per quarter.

From the long run relationship the ECT_{t-1} term can be derived as described by Enders (1995), detailed in the VEC estimation section in the appendix. The following equation is obtained:

$$ECT_{t-1} = 1.00top\,1WS + 0.4063459FR - 0.0152268log(sp500) - 0.2389484 \quad (4.5)$$

Note that the signs need to be reversed when interpreting the ECT_{t-1}.

In sum, judging from the obtained results, the question whether the federal funds rate affects wealth inequality can thus be answered in the affirmative. A decrease in the federal funds rate is associated with a positive effect on wealth inequality in the long run.

4.5 A short-run analysis, A Vector autoregressive model

The aim of the thesis is to investigate the effect of macroeconomic variables on wealth concentration, as a representative of wealth inequality. Initially, this means looking for a long-term relationship between wealth inequality and the chosen macroeconomic variables. Since most of the collected variables, representing various channels of effect, did not display cointegrated relationships with wealth inequality a different model is necessary to understand whether these channels have some effect on wealth concentration. Furthermore, since patents and unemployment were included to reflect long-term effects these can be excluded from the short-run analysis in favor of looking more closely at the other effects.

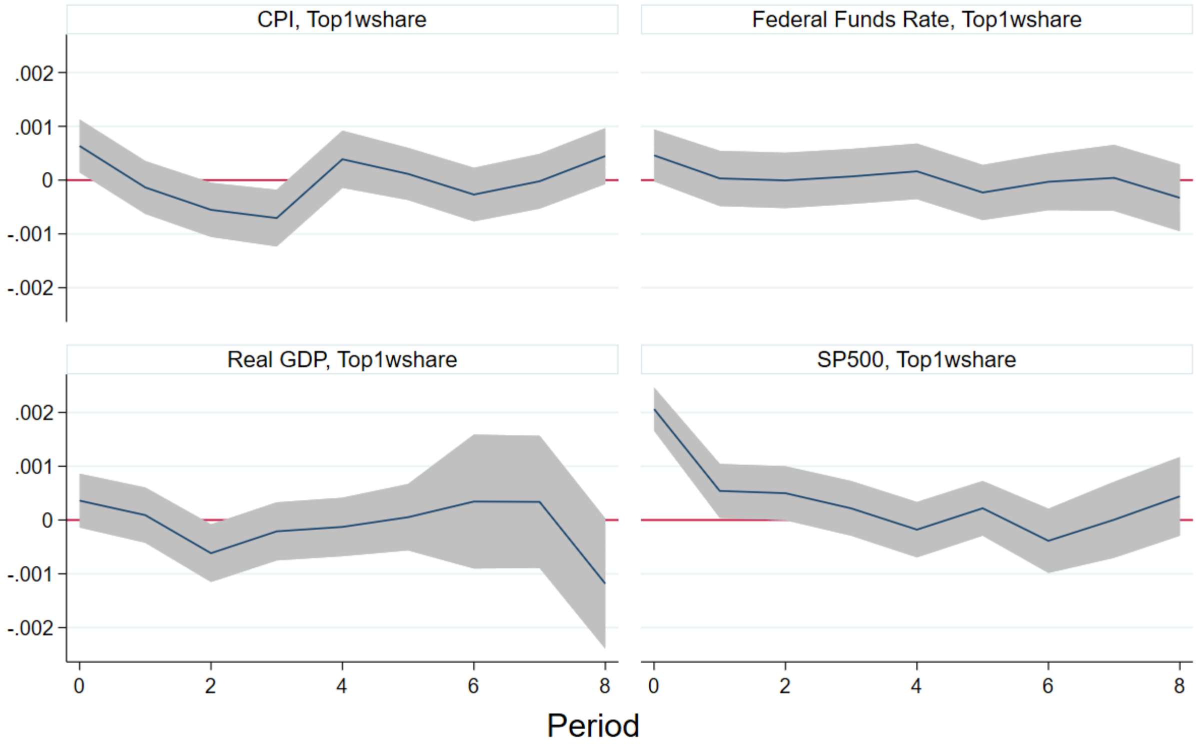
The VAR framework was elected as a secondary model for the thesis. The VAR model is particularly useful since it accounts for endogeneity, allowing for cross-relationships over the variables, similar to the Vector Error Correction model. A Vector autoregressive can be expressed through a vector moving average. The VMA methodology further allows for tracing the paths of the variables in the model (Enders, 1995). Although the mathematics behind the vector moving average method will not be delved into, the paper will apply it as an illustrative and informative tool in the empirical analysis part. The standard VAR model can not easily implement this, however, as the estimated VAR is under-identified and therefore necessitates an identification restriction. An often used restriction is the Cholesky decomposition, which, simply stated, restricts the contemporaneous effect on the main dependent variable (Enders, 1995). The contemporaneous restriction that is to be imposed in this study is similar to that used by Davtyan (2017), who argues that the variable for the policy rate is assumed to not be contemporaneously affected by income inequality while being contemporaneously affected by both output and prices. Subsequently, the variable for income inequality is assumed to be contemporaneously affected by all other variables. While this study does not look at income inequality, a similar restriction is imposed for which we assume a similar scheme but replace income with wealth inequality. Furthermore, we assume that the S&P500 index is contemporaneously affected by all variables except wealth inequality, as we assume an efficient market will respond instantly to changes in the economy.

By applying ordinary least squares the model can interpret the data. Each variable in the system of equations is affected by both its own lagged value as well as the lagged values of the other variables in the system. The VAR function can then be written in a concise form, following the example by Davtyan (2017)

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{4.6}$$

in which Y represents the vector of endogenous variables, A represents the time-invariant (*k x k)*-matrix of unknown parameters. The error term can be defined as the white noise, where there is constant mean and variance assumed as well it is assumed to be independently distributed: no autocorrelation (this will be tested later in the thesis). The error term can also be expressed as the "surprise" term from which it can be inferred how the variables are affected by shocks in the other additional variables. A recursive VAR (as opposed to the reduced form) assumes no correlation between the error and the errors from previous equations (Stock and Watson, 2001). Additionally, all the variables are used in their first difference forms. This allows for stationarity in the variables (as displayed in the section unit roots) and the log transformation enabling interpretations of elasticities.

Figure 2 - *Impulse responses*



Note: The figure represents the 4 different orthogonalized impulse responses. It follows the convention of the impulse variable being comma separated from the response variable. The shaded area outlines the 95% confidence interval and the zero line is marked with red.

The results of the vector autoregressive model were in some parts similar to that of the vector error correction model, however, they do not of course look at the same timeframe. Whereas the previous analysis was meant to capture the long-term effect the VAR analysis aims to capture the short-run effects. The response functions can be interpreted as a one-unit shock to the affected variable. In the case of this study, the main focus is wealth concentration, meaning there will be four responses. The gray area reflects the 95 % confidence interval indicating that if the gray area encompasses the red line for the entire duration, no significant response can be read from a one-unit impulse.

In the figure above the first graph on the first row displays the effect of a one unit shock from the consumer price index (differenced), on wealth concentration. As can be observed, the impulse prompts a small positive initial response, whereafter the effect is insignificant but the response reappears briefly after two quarters where it is negative. The second graph on the first row displays the effect of the federal funds rate, which is insignificant for the entire duration and therefore can not be interpreted as having a short-term effect on wealth concentration. The first graph of the second row displays the effect of a one-unit increase in real GDP. There is only a minor negative effect after two quarters. The second graph on the second row reflects the impact of a one-unit shock on the S&P500 and its impact on wealth concentration. As can be readily observed, of the four impulses, this is the one that generated the clearest response. The impulse on the S&P 500 displays a clearer initial positive short-run impact on wealth concentration. Similar to the other responses, the effect quickly diminishes and is insignificant after only one quarter.

Both the VEC and the VAR models display effects from the market index. The vector autoregressive model displays significant effects both from inflation, real GDP, and the market index. However, the effects are barely significant for two out of three while the market index seems to have a greater initial impact on wealth concentration. The ordering was further changed to test the robustness of the Cholesky imposed impulse responses. While the placement of the federal funds rate, the market index, and the wealth variable were held constant, both prices and output were reordered. Additionally, as the federal fund rate can be seen as slow to adjust to changes, the model was reordered with the rate not being contemporaneously affected by any other variable, while all other variables were affected by it. These changes did not impact the significance of inflation or S&P500, however, reversing the order between inflation and real GDP removed the significance of real GDP, which disconcert its effect on wealth concentration. A benefit of the quarterly data on wealth is that no other transformation of the variable is needed to increase the frequency of the data. Davtyan (2017) utilizes mainly a Gini index which is only annual. As we are using quarterly data we are able to utilize the restriction more easily, however, as our wealth concentration variable is not a standard inequality index, the representation of the variable may not be as useful in terms of capturing an overall increase in inequality.

4.6 Post estimation

In order to establish the true capability of the model, testing must be done to ascertain the functionality of the model for the data. When the post-diagnostics are insufficient the model may have to be remade, either by transforming, removing, or changing variables, or readjusting lag length. To correctly establish the model tests for normality, as well as autocorrelation in residuals are to be performed.

No autocorrelation in the residuals is the first of the assumptions underlying the model. A violation in the assumption would imply that the least square estimator would no longer be the best linear estimator. The assumption can also be expressed as: the conditional mean of the residuals is zero and a violation would imply that residuals from a previous period can explain the present period (Stock and Watson, 2015). To test for autocorrelation for the vector models this thesis applies a Lagrange Multiplier (LM) test as proposed by the stata guide and presented by Johansen (1995). Furthermore, in order to obtain a reliable estimate the residuals must be tested for *normality.* If the residuals do not reflect normality the method may not use the t-test as well as the f-test in order to receive correct estimates using ordinary least squares, leading to an overall misinterpretation by the model (Jarque and Bera, 1987). This following section will briefly discuss the robustness tests carried out for the VEC and VAR models.

4.6.1 Autocorrelation

Table 7 below lists the results from the autocorrelation test for the VEC model and table 8 below lists the results for VAR models. The null hypothesis is that there is no autocorrelation at the chosen lag length. As discussed earlier there is potentially a tradeoff when deciding on the number of lags. With too few lags the model runs the risk of suffering from autocorrelation but including many lags has the corollary of the coefficients quickly proliferating, which is especially undesirable with limited observations. The null hypothesis cannot be rejected for the VEC model for either of the 8 lags, there is thus no autocorrelation present. Although for the VAR model for the fifth lag the null hypothesis is rejected, indicating that the fifth lag exhibits some autocorrelation.

Table 7 - *Lagrange multiplier autocorrelation test for the VEC model*

H_0: there is no autocorrelation

H_1: there is autocorrelation

lag	*chi2*	*df*	*prob > chi2*
1	*9.0174*	*9*	*0.43567*
2	*11.0569*	*9*	*0.27183*
3	*7.2096*	*9*	*0.61530*
4	*10.1177*	*9*	*0.34104*
5	*14.1824*	*9*	*0.11598*
6	*9.7104*	*9*	*0.37444*
7	*7.9559*	*9*	*0.53860*
8	*6.2419*	*9*	*0.71549*

Table 8 - *Lagrange multiplier autocorrelation test for the VAR model*

H_0: there is no autocorrelation

H_1: there is autocorrelation

lag	*chi2*	*df*	*prob > chi2*
1	*27.5305*	*25*	*0.32991*
2	*19.6611*	*25*	*0.76437*
3	*27.2495*	*25*	*0.34354*
4	*29.2868*	*25*	*0.25210*
5	*41.4837*	*25*	*0.02041*
6	*16.1387*	*25*	*0.91064*
7	*17.5123*	*25*	*0.86238*
8	*26.2435*	*25*	*0.39470*

4.6.2 Normality

Table 9 below represents the results from the Jarque-Bera normality test of the residuals for the VEC model and the VAR test results can be found in table 10. The null hypothesis is that the residuals are normally distributed and the alternative hypothesis is that the residuals are non-normally distributed. For most of the residuals for both the VEC and VAR models, the null hypothesis is rejected at the 5% level, indicating that the error terms appear non-normally distributed. In the VEC model the only function that was neither rejected at the 5 nor at the 10 % level was the S&P500, indicating that the normally distributed residuals assumption cannot be rejected. Similarly, in the VAR model the only function that was neither rejected at the 5 nor at the 10 % level was the S&P500 and the top 1 percentile's wealth share. These test results may entail that the results from the VAR and VEC models turn out less reliable. However, it has been suggested that if the sample size is sufficiently large the normality assumption may not be required as the effect of non-normality may not be as substantial (Lumley et al. (2002). Schmidt and Finan (2018) further argue that assuming that the observations per variable is greater than 10, non-normality does not have a large impact on the results.

Table 9 - *Jarque-Bera normality test for the VEC model*

H_0: $Normally\ distributed\ residuals$

H_1: $Non\ normally\ distributed\ residuals$

Equation			
top 1 percentile's wealth share	*16.834*	*2*	*0.00022*
federal funds rate	*30.000*	*2*	*0.00000*
S&P 500	*0.926*	*2*	*0.62947*
ALL	*47.760*	*6*	*0.00000*

Table 10 - *Jarque-Bera normality test for the VAR model*

H_0: *Normally distributed residuals*

H_1: *Non normally distributed residuals*

Equation	*chi2*	*df*	*Prob > chi2*
Real GDP	*2924.270*	*2*	*0.00000*
CPI	*120.600*	*2*	*0.00000*
Federal Funds Rate	*20.833*	*2*	*0.00003*
SP500	*2.661*	*2*	*0.26439*
Top 1 Percentile's Wealth Share	*0.914*	*2*	*0.63324*
ALL	*3069.278*	*2*	*0.00000*

5. Discussion

This thesis has sought to better comprehend and describe the effect of monetary policy on wealth inequality, understood through its channels of effect. Additionally, this thesis aimed to further explain the effect of innovation on wealth inequality, a relationship previously investigated by Giri et al. (2021) in the context of income inequality. This thesis mainly employs a Vector Error Correction model to investigate the long run dynamics of the relationships, but additionally includes a VAR model in order to investigate, in the short run, the factors that did not exhibit a long run cointegrating relationship. The results accord with much of the findings from previous literature. The long run results from the VEC model suggest that the SP500 index increases wealth inequality, as does an expansionary monetary policy, i.e., for wealth inequality as measured by the top 1 percentiles wealthshare. The results are in line with that of Albert et al. (2020) where the portfolio channel was found to increase wealth inequality. Further, the effect from the federal funds rate is in accordance with the discussion presented by Colciago et al. 2019.

The restricted VAR framework displayed a significant positive impact at the 5% level on wealth inequality with respect to the market index and the federal funds rate. The results are in line with what was recently proposed by Albert et al. (2020) who utilized the Bayesian proxy SVAR framework and concluded that mainly the portfolio channel had an impact on wealth inequality. The additional significant impact from the change in the interest rate confirms the prior belief that monetary policy affects wealth inequality, however, the results are slightly weaker compared to the market index, which favors the argument that monetary policy possibly only has a minor impact on inequality, as proposed by Bernanke (2015). Furthermore, two of the other factors proved significant in the VAR framework. While the effect of real GDP is questionable, as it proved insignificant in one case during our robustness check, inflation proved significant in all checks. The effect of inflation was unsurprising as it is greatly discussed in the litterature. The movement of the effect from positive to negative is another point of discussion. The initial movement could potentially enforce the generally accepted belief that inflation has an expanding effect on wealth inequality, as proposed by Colciago et al. (2019). The sequentially negative effect may favor the studies which have argued for slightly positive effects, such as Menna and Tirelli (2017), Doepke and Schneider (2006). The varied results point towards the effect of inflation rather being of an ambiguous nature, and the importance of separating the effect further. The significant impact of the market index on inequality is similar to the effect described in the restricted vector-autoregression framework. This further validates the belief concerning the portfolio channel having a distinct impact on inequality. The result is similar to that of Albert et al. (2020) and Alves and Thomás (2021) who used slightly different methods as well as investigated different areas. The similarities to Albert et al. (2020) were expected as they look at the same area. However, Alves and Thomás (2021) with their the extension assessing the Eurozone area further reinforces previous claims of the importance of the market on inequality

5.1 Limitations

Furthermore, there are some important limitations of this study that need to be addressed. The number of observations is relatively low given how the VEC and VAR models are constructed, although this is common in macroeconomic studies and the observation count is by no means particularly lower than many other studies in the field. In fact, given the difficulty of procuring any wealth data at all, the data quality can surely be considered more than adequate. Given the interrelationship between the variables, VAR and VEC models were required to account for endogeneity. A drawback associated with the models then is the restriction with respect to the relatively low number of explanatory factors that are considered. Control variables in the strict sense that is common in OLS and other similar frameworks do not pertain to VAR models as the variables included need to be closely related within the system. The number of variables included in this study may already verge on being too high, even though not all factors affecting wealth inequality are included. As discussed in the lag selection, adding too many variables will increase the number of coefficients relative to the number of observations, which will decrease the degrees of freedom. Naturally, to get as many observations as possible and to cover as long a relevant period as possible the time span dates to 1989. Several changes have occurred since then, which could be considered structural breaks. In accordance with what was considered in the literature, it is hard to measure and account for everything at once and while still keeping the variable count to a minimum, this potentially constitutes a limitation as well. Furthermore, without controlling for structural breaks there is a distinct possibility that some of the effects presented in the results could be attributed to other sources than those hypothesized in the thesis. The potential problem posed by omitted factors does not necessarily pertain merely to economic fluctuations, which transpires reading the literature section of the paper, as not all channels of effect or factors included in previous studies could be fully represented in this thesis. For instance, the income composition channel, the financial segmentation channel, and the housing channels are all channels that may affect inequality, as suggested by previous research. Additionally, the channels represented in the thesis are not necessarily the best representations for their sources. For instance, the choice of patents as a vehicle for innovation may be less valuable compared to other representations of innovation, such as an index. Though it should be reiterated that no data on some quarterly index up to date or similar could be found during the data collection of this thesis. In a similar manner, the data may not be sufficient to analyze changes in wealth between households, as the data is based on the macro rather than microdata. The choice of macro allows for greater data availability but reduces the ability to differentiate between households. Due to this, channels such as the portfolio channel intended to capture the effect of increased ownership in the market, may not be adequately representative of the increased change in inequality, since there is no data on specific household wealth.

6. Conclusion

The purpose of this paper has been to both describe and further explain the development of wealth inequality and how wealth inequality is affected by monetary policy. In order to extend the analysis the paper utilizes both the vector autoregressive model with impulse response functions, as well the vector error correction model, with the hypothesis that monetary policy shares a long-run equilibrium with wealth inequality. In addition to the previously studied distributional channels of monetary policy the paper further describes the effect of innovation on wealth inequality. The result of the VAR framework was a positive significant impact from both the market index as well as the consumer price index on the wealth owned by the top 1 percent. A result somewhat in line with what was previously described concerning the effect of the portfolio channel as well as the unexpected inflation channel on wealth inequality. Similarly, the Vector Error Correction model displayed a significant long-run relationship between wealth and the market index as well as wealth and the federal funds rate. However, the results from the tests were not perfect as the residuals may experience non-normality, which could lessen the accurateness of the results. In the final tests only the function for the market index displayed normally distributed errors. The findings emphasizes the importance of the market and reinforced the prior belief that the portfolio channel may be the most influential concerning wealth distribution.

As the purpose of this thesis is but to quantify effects on wealth inequality, particularly the federal funds rate, a neutral stance as to policy suggestions will be assumed. Were there definitive results as to the distributive effects of monetary policy throughout the literature as well as in this study, coupled with a consensus, there could well be more significant policy implications. This thesis, for one, can serve as an important building block to extend upon for future research. Acknowledging the difficulties associated with accounting for all relevant factors simultaneously, encountered in this thesis as well as proffered by Colciago et al. (2019) amongst others, making more holistic studies could be a way forward and thus is a suggestion for future research. To make way for such studies, considerably better datasets should be made, whether they be created by capitalizing on income or by some government action to more extensively collect wealth data. There could then form a consensus rooted in empirical evidence that can guide policy decisions and considerations more accurately in the United States as well as in other countries.

The thesis is aimed at looking at the distributional effects of monetary policy and the factors that affect wealth inequality. It does not question the focus of current monetary policy but merely seeks to determine its effects on inequality and extends previous literature by adding innovation as an explanatory factor. The paper serves an informational purpose for policymakers on the distributional power of monetary policy and its effect on inequality.

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Appendices

Appendix 1: Variables and graphical illustration.

Following previous research a VAR and a VEC model is applied as these two models allow for endogeneity between variables. In utilizing such models the thesis assumes that the variables are all fairly closely related, which highlights the importance of the following descriptive section.

The following 7 graphs or figures presented below reflect the development of the variables over time. As previously mentioned, the increase in the wealth share owned by the top 1 percent has seen a more dramatic increase compared to the top 10 percent. While the top 1 percent has increased to approximately 32 % as of 2021 the top 10 percent has experienced a lesser increase. The latter has a substantially larger portion as of 1989 but has since then not increased substantially. Comparable during the same time period, both real GDP and the CPI have experienced almost constant growth over time. The market index seems more akin to the developments of utility patents, for both variables experienced slower growth up until around 2010 when both started increasing substantially. Lastly, unemployment seems to have been experiencing a trend of overall larger increases followed by overall reductions, finishing somewhere near the initial level of unemployment in 1989. It is apparent looking at the graphs that the variables do not tend to be stationary, leading us to transform the variables in order to be able to utilize the VAR framework as well as the VEC framework. The following section will go further into explaining the variables. Each will begin with an introduction as to why the variable was chosen, wherafter the specification of the variable is described.

Introduction to and motivation behind the variables

The following section includes the collection and motivation behind the choice of variables. The former part of each variable briefly explains the motivation, whereafter the method of collecting the variable is further explained.

Consumer price index

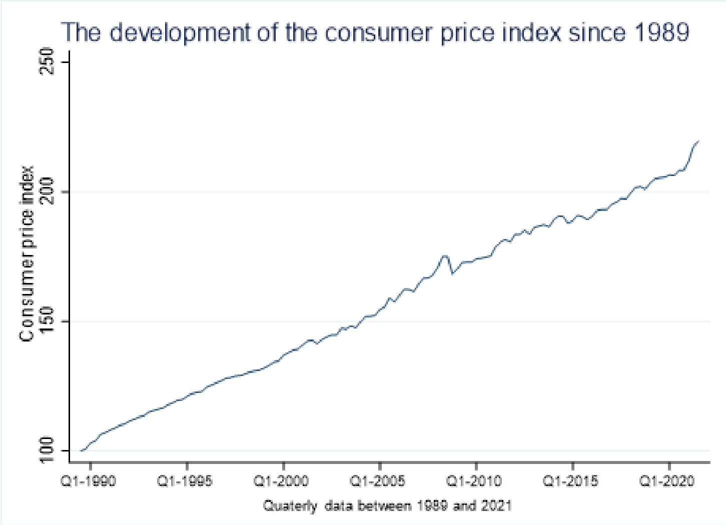
A Consumer Price Index was employed in this thesis for the generation of the inflation variable. Inflation, which is also described through the savings channel, is greatly expounded on in the field. Several researchers have investigated its effect and, as expressed by Colciago et al. (2019), the general consensus is that inflation tends to increase inequality. There are, however, papers that have produced different results such as Siami-Namini and Hudson (2019) as well as an important paper produced by Doepke and Schneider in 2006, which enforces the ambiguous nature of the variable. In those papers an increase in inflation is believed to reduce wealth inequality but that there are mitigating factors which may lessen the effect on inflation.

Specifically, the Consumer Price Index for All Urban Consumers is the one used, which was retrieved from the Federal Reserve Bank of s.t Luis, originally from the U.S Bureau of Labor Statistics. The CPI comprehends the vast majority of the US population ranging from different types of wage earners to the unemployed and the retired population. It reflects the relevant basket of goods, any given quarter, consisting of items such as food expenditures, residency expenditures, fuels, fares, etc. where each item is weighted depending on its importance to accurately reflect price levels of any given quarter. Likewise is this CPI the index of most pertinence as categorized by relevance on the federal reserve of s.t Luis (FRED, 2021). Employing this CPI, the inflation variable was generated thus:

$$\pi_t = log\left(\frac{P_t}{P_{t-1}}\right) \quad (A.1)$$

Where π_t denotes the inflation in time period t, P_t denotes the price level in time period t and, naturally, P_{t-1} denotes the price level in the previous period. The variable is logged and the variable represents the percentage change in prices. This variable is thus generated using the first difference of the logged price levels of the two consecutive time periods.

Figure A.1



Share of total wealth owned by the top 1 and 10 percent

The share of total wealth owned by the top percentile intends to capture wealth inequality, as an increase in this variable implies that the remainder of the population will possess less of the total wealth in the economy. This variable constitutes the main dependent variable, though given the type of model and the endogenous system, each variable is considered a form of dependent variable. The variable was chosen due to the lack of quarterly data on the Gini index for wealth inequality, which was one reason that prompted the inclusion of the distribution of the top 1 and top 10 percent variables. The adoption of the top 1 percent as the variable representing wealth inequality has been previously represented by Albert et al. (2020), in a similar study looking into the effects of income and wealth inequality.

The data was retrieved from the federal reserve of s.t Luis, though it originally comes from the quarterly Distributional Financial Accounts of the United States. The Distributional Financial Account's data series is available from the third quarter of 1989 until the third quarter of 2021 and thus contains 129 periods in total thus far. There are some technicalities (which will be omitted) underlying this dataset by the Board of Governors of the Federal Reserve; technically, it is derived from a type of amalgamation of the Survey of Consumer of Finances and the Financial Accounts of the United States. For brevity the change in the top percentile's wealth share will use the following naming convention:

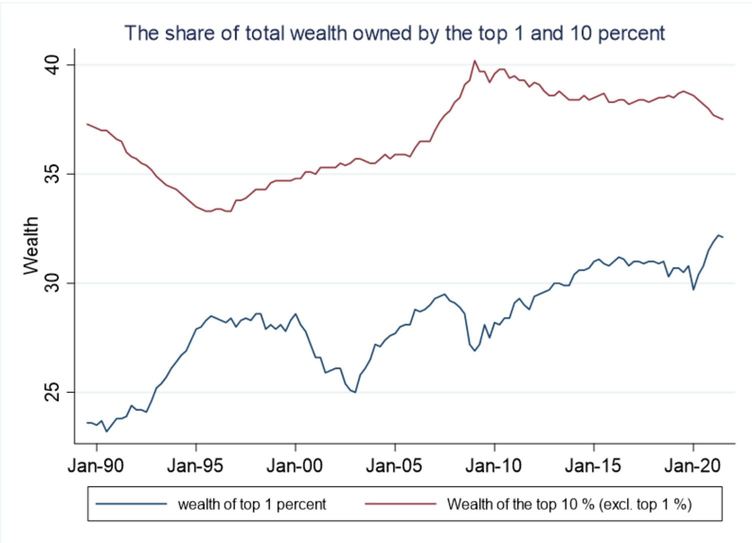
$$W_t = w_t - w_{t-1} \tag{A.2}$$

Where w_t denotes the top 1 percentiles wealth share in time period 1, w_{t-1} denotes the top 1 percentile wealth share in the time period $t - 1$. Since the variable is already in percentage form simply taking the difference in the 1 percentiles wealth share the change over time is obtained, denoted W_t for brevity.

Likewise, is the top 10 percentile's wealth share used in this thesis as an ancillary main dependent variable as a substitute for the top 1 percentile's wealth share, permitting ready comparison of these 2 percentile's growths and possibly enabling for shedding light on reasons conducive to these differences. The 10 percentile's wealth share was retrieved directly from the Federal Reserves' website. The variable will use the following naming convention:

$$W^{10}_{t} = w^{10}_{t} - w^{10}_{t-1} \qquad \text{(A.3)}$$

Figure A.2



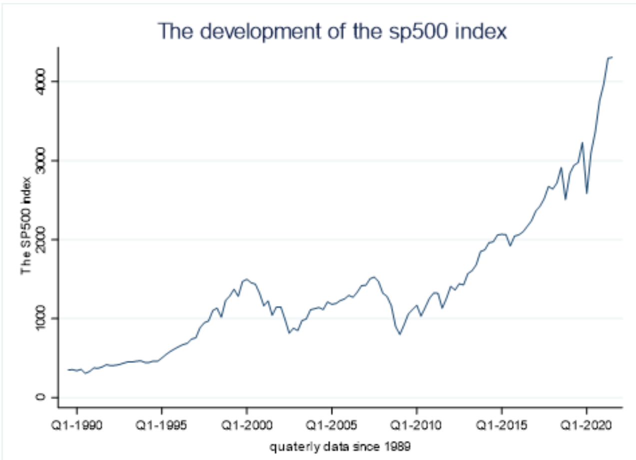
The market index, S&P500

S&P500 (Standard & Poor's 500), the prominent large-cap index covering 500 heavily traded American stocks, is also used in the VEC/VAR model. The variable is meant to represent the effect of the portfolio channel, which assumes that the wealthier in society owns a larger part of the market, i.e., a larger part of their wealth in financial assets. The variable was previously used in a similar fashion, representing the portfolio channel, in a study by Albert et al. (2020). The conjecture would be that a positive change in S&P 500 will be conducive to a positive effect on wealth inequality, represented through the wealth owned by the 1 and top 10 percent. Several other papers have discussed the portfolio channel including a well known previously cited article by Coibion et al. (2020).

The data was retrieved from investing.com on account of its readily available data and ease of use. The return was generated as such:

$$R_t = log(\frac{sp500_t}{sp500_{t-1}}) \quad (A.4)$$

Figure A.3



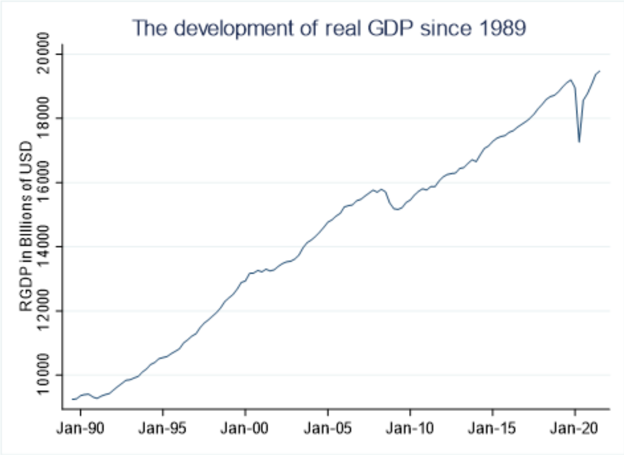
Real GDP

One of the reasons for the inclusion of the real GDP was since it was considered likely for there to exist a relationship between real GDP and economic inequality. The belief was further enforced by previous studies by Siami-Namini and Hudson (2019) and Zheng et al. (2020) that have further expressed the relationship between economic growth and economic inequality and its close connection to inflation. Similar to the market index, an increase in economic growth is expected to induce an increase in inequality rather than a decrease.

The data for real GDP was collected from the Federal Reserve Bank of st Luis, stemming from the U.S Bureau of economic analysis. By the same token, the percentage change in real GDP was likewise obtained by taking the first difference of the logged values:

$$G_t = log(\frac{rgdp_t}{rgdp_{t-1}}) \quad (A.5)$$

Figure A.4



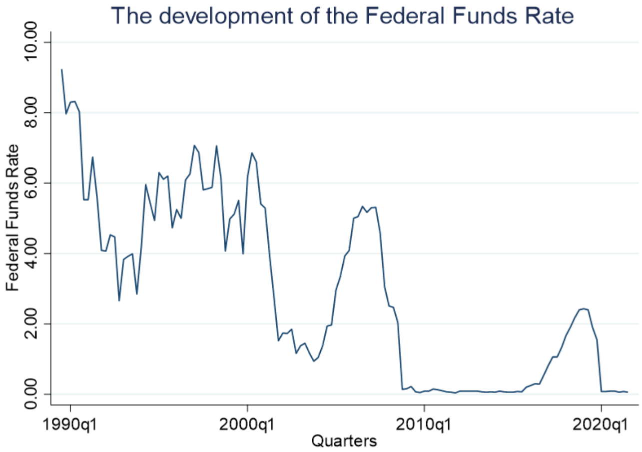
The federal funds rate

The most significant tool the Federal Reserve has at its disposal with respect to conducting monetary policy is the Federal Funds Rate. This is the rate at which banks can borrow overnight from the central bank. Regulating this rate, the federal reserve can effectuate changes in interest rates throughout the economy and likewise influence the money supply, unemployment, and inflation over time (FED, 2021). As a proxy for monetary policy in this thesis the Effective Federal Funds Rate was thus used:

$$F_t = ffundsr_t - ffundsr_{t-1} \quad \text{(A.6)}$$

Again, the variable is already defined in percentages and needs not be manipulated further to reflect the relevant change.

Figure A.5



Innovation variable

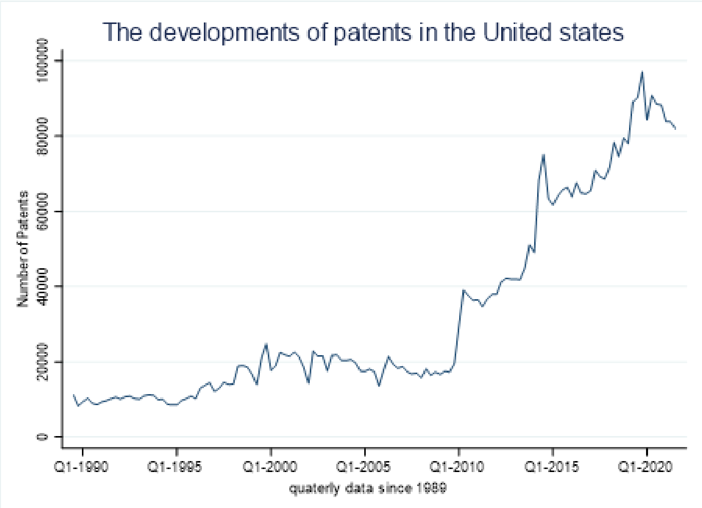
As a proxy for innovation, the number of patents in any given period was used with respect to the issue date. Specifically, a utility patent is the elected type of patent, or as it commonly is referred to, "patent for invention" (US Patent and Trademark Office, 2016). Patents as a proxy for technology or innovation can be found in the literature e.g., Giri, Pandey, and Mohapatra (2020) assess the impact of, inter alia, technology on the Gini coefficient for income. One of the variables they use to reflect technological change is the number of patents. The patent variable can be found in disparate settings as well, such as Jalles (2010) where the patent variable and the intellectual property rights index were used as a proxy for technological change in their OLS framework for determining economic growth. While it would be useful to include a variable such as the intellectual property right's index, such variables typically are not available as quarterly data for extended periods of time or for the most recent years. It is also a question of parsimony, as the number of variables should be kept low in a VAR framework (Stock and Watson, 2015).

The innovation variable is hence constructed as follows:

$$I_t = log(\frac{PAT_t}{PAT_{t-1}}) \quad (A.7)$$

Where PAT_t denotes the number of patents at time period t and PAT_{t-1} denotes the number of patents in time period $t - 1$.

Figure A.6



Unemployment variable

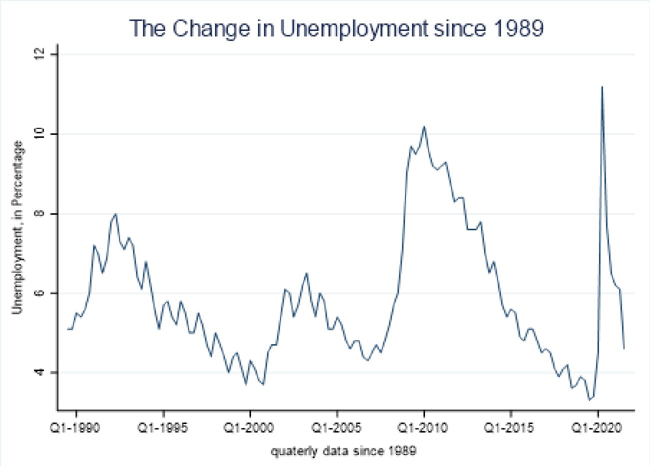
The unemployment variable was chosen as to be representative of the earnings heterogeneity channel, where the argument is that households that have less stable jobs are more harshly affected by a reductive monetary policy, and as these households tend to be at lower wealth brackets, this would be conducive to an increase in inequality (Coibion et al. 2017). The variable is thus believed to have a positive relationship with wealth inequality.

The unemployment variable was also retrieved from the Federal Reserve Bank of st Luis, though it originally stems from United States Bureau of Labor Statistics. It is defined as how many unemployed there are out of the total labor force, where in turn the labor force comprehends those of age 16 or higher that do not live in institutions such as retirement homes, prisons, asylums, and in addition, do not hold a position of active service in the U.S military. The unemployment variable is defined thus:

$$U_t = u_t - u_{t-1} \quad \text{(A.8)}$$

Where u_t denotes the unemployment rate at time period t, u_{t-1} denotes the unemployment rate at time period $t - 1$, and U_t denotes the change in unemployment. By retrieving the variable already in percentage form, just like for the wealth variables and the federal funds rate, the need for further manipulation was obviated.

Figure A.7



Appendix 2: The Vector Error Correction Model and the Vector autoregressive model

As the VEC is an extension of the VAR model it makes sense, as a point of departure, to commence with a VAR model. A VAR model can be expressed thus:

The Vector Autoregression Model

(A.9)

$$y_{1,t} = \mu_1 + \sum_{i=1}^{p} \theta_{11i} y_{1,t-i} + \sum_{i=1}^{p} \theta_{12i} y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{1ki} y_{k,t-i} + \varepsilon_{1t}$$

$$y_{2,t} = \mu_2 + \sum_{i=1}^{p} \theta_{21i} y_{1,t-i} + \sum_{i=1}^{p} \theta_{22i} y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{2ki} y_{k,t-i} + \varepsilon_{2t}$$

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$$y_{k,t} = \mu_k + \sum_{i=1}^{p} \theta_{k1i} y_{1,t-i} + \sum_{i=1}^{p} \theta_{k2i} y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{kki} y_{k,t-i} + \varepsilon_{kt}$$

in which there is a k number of linear equations with *p* order of lags, where y_i terms denote the dependent variables in the system, t denotes time of a variable and the θ terms are just coefficients to be estimated. The var model is thus a system of equations where each dependent variable is a function of its own lags and the other lagged dependent variables. The VAR, however, does not incorporate the presence of a long-run relationship between variables. To account for a long-run relationship between variables and investigate the specifics of the model and thus short-term deviations from the long run, a VAR is extended to a VEC model by first taking the first difference of the variables, enabling for stationarity, and then including an ECT_{t-1} term to allow for a return towards the long run.

The long run, first and foremost, needs to be estimated. The long run for the VECM can be estimated by regressing the dependent variables on the elected main dependent variable of choice, i.e., either of the dependent variables can be chosen to be on the left-hand side. The long run can thus be taken from step 2 of the 4 step process. E.g., if there are 6 dependent variables the long-run relationship can be determined as follows:

$$y_{6t} = \psi_0 + \psi_1 y_{1t} + \psi_2 y_{2t} + \psi_3 y_{3t} + \psi_4 y_{4t} + \psi_5 y_{5t} + \varepsilon_t \quad \text{(A.10)}$$

from which the error term or ECT term can be extracted:

$$ECT_t = - y_{6t} - \psi_0 - \psi_1 y_{1t} - \psi_2 y_{2t} - \psi_3 y_{3t} - \psi_4 y_{4t} - \psi_5 y_{5t}$$

$$ECT_{t-1} = - y_{6t-1} - \psi_0 - \psi_1 y_{1t-1} - \psi_2 y_{2t-1} - \psi_3 y_{3t-1} - \psi_4 y_{4t-1} - \psi_5 y_{5t-1}$$

Including these steps together the VAR is rendered into VEC model and will thus take on the following form:

(A.11)

$$\Delta y_{1,t} = \mu_1 + \sum_{i}^{p} \theta_{11i} \Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{12i} \Delta y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{1ki} \Delta y_{k,t-i} + \delta_1 ECT_{t-1} + \varepsilon_{1t}$$

$$\Delta y_{2,t} = \mu_2 + \sum_{i=1}^{p} \theta_{21i} \Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{22i} \Delta y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{2ki} \Delta y_{k,t-i} + \delta_2 ECT_{t-1} + \varepsilon_{2t}$$

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$$\Delta y_{k,t} = \mu_k + \sum_{i=1}^{p} \theta_{k1i} \Delta y_{1,t-i} + \sum_{i=1}^{p} \theta_{k2i} \Delta y_{2,t-i} \dots + \sum_{i=1}^{p} \theta_{kki} \Delta y_{k,t-i} + \delta_k ECT_{t-1} + \varepsilon_{kt}$$

As before, the k variable denotes the quantity of variables in the VEC model, the t term simply denotes the time period and p denotes the lag length.

Table A.1 - VEC coefficients

Variables	***Top 1wshare***	***Federal funds rate***	***S&P 500***
CE_L1.	*-.1281745** *(.0411308)*	*-.0661699* *(.0679616)*	*-.2890836* *(.9393654)*
_cons	*-.0064176** *(.0022449)*	*-.0046348* *(.0037093)*	*.0039063* *(.0512703)*
Top1wshare			
LD.	*-.2205038* *(.1554958)*	*.3484419* *(.2569304)*	*-5.297867* *(3.551291)*
L2D.	*.0791227* *(.1577599)*	*.1421238* *(.2606714)*	*.5489735* *(3.602999)*
L3D.	*-.0085129* *(.1539459)*	*.0817193* *(.2543695)*	*-3.300019* *(3.515895)*
L4D.	*.1929199* *(.1540316)*	*-.0381177* *(.2545111)*	*-5.180307* *(3.517852)*
L5D.	*.0789921* *(.1587111)*	*.0659487* *(.2622431)*	*.061594* *(3.624724)*
L6D.	*.1477331* *(.1564395)*	*.1994724* *(.2584897)*	*4.418192* *(3.572844)*
L7D.	*.0065975* *(.1568939)*	*-.109372* *(.2592406)*	*3.911853* *(3.583222)*
L8D.	*.2759688* *(.1549998)*	*.0476236* *(.2561109)*	*1.204128* *(3.539964)*
Ffundsr			
LD.	*.0904655* *(.0651975)*	*.0452908* *(.1077278)*	*1.438915* *(1.489014)*
L2D.	*.0225009* *(.0645892)*	*.1217873* *(.1067227)*	*.2032814* *(1.47512)*
L3D.	*.0038665* *(.0593403)*	*-.091201* *(.0980498)*	*1.535338* *(1.355244)*
L4D.	*.0654461* *(.0568567)*	*.2945764* *(.093946)*	*1.615543* *(1.298521)*
L5D.	*.0035765* *(.057576)*	*-.0760078* *(.0951346)*	*-.1005754* *(1.314951)*
L6D.	*.0038702* *(.056764)*	*-.2814324* *(.0937929)*	*-.7728988* *(1.296406)*
L7D.	*.0623203* *(.0612188)*	*.0774625* *(.1011537)*	*.142222* *(1.398147)*
L8D.	*-.0602139* *(.0613158)*	*.1270916* *(.101314)*	*-2.428148* *(1.400362)*
S&P500			
LD.	*.017101** *(.007134)*	*.0076218* *(.0117878)*	*.1660866* *(.162931)*

L2D.	*.0044929* *(.0072534)*	*-.0005855* *(.0119851)*	*.0681409* *(.1656577)*
L3D.	*.0030388* *(.0070455)*	*-.0012694* *(.0116415)*	*.1233858* *(.1609093)*
L4D.	*-.0056623* *(.0069485)*	*.0002239* *(.0114813)*	*.1608133* *(.158694)*
L5D.	*.001202* *(.0068007)*	*.0154095* *(.011237)*	*.1096804* *(.1553178)*
L6D.	*-.0070347* *(.0067612)*	*-.007898* *(.0111717)*	*-.0724662* *(.1544159)*
L7D.	*-.0014023* *(.0067939)*	*.0053628* *(.0112258)*	*-.2637164* *(.1551629)*
L8D.	*-.001611* *(.0068979)*	*-.0001049* *(.0113976)*	*-.0625083* *(.157538)*

(standard errors in parentheses)

* p< 0.05

Table A.2 - VAR coefficients

Variables	Real GDP	CPI	Federal Funds Rate	S&P500	Top1wshare
Real GDP					
L1.	-.2255131*	.0161432	.0281543	-.0111193	.0069086
L2.	-.2452112*	.0804443	.02387	-1.037164	-.0593655*
L3.	-.0600484	.0416087	.0966233	-.831728	-.0196601
L4.	-.1034942	-.1360631*	-.0041959	-.7984876	.0015874
L5.	-.0841012	-.1339273*	.0824829	-.7975193	.0254586
L6.	.422841	.1279366	-.0589065	2.896299	.0392431
L7.	.1089325	.3031139	.0446878	.0628841	-.0487047
L8.	.1263911	-.1651572	.0918279	-2.562581	-.105265
CPI					
L1.	.0073966	-.0460644	-.1191259	-.2115593	-.0223474
L2.	.1433627	-.2781771*	-.1204139	-3.325936*	-.1349999*
L3.	.0272686	-.0902712	-.0448363	-2.554845*	-.1240386*
L4.	.1653488	.1251452	-.0190482	-1.941127	.0723345
L5.	-.1465414	-.0850954	-.1453488	1.732289	.0885425
L6.	.1279568	.0384895	-.0585963	.1652752	-.0483261
L7.	-.0005496	.012575	-.1267504	-.5408312	-.0279506
L8.	-.0228571	.2598854*	.0954327	.1204883	.0172817

Ffundsr					
L1.	.5289743*	.0007436	.0002952	1.104034	.0102772
L2.	-.007385	.0700931	.0562897	.4467998	-.0473716
L3.	.2239938	-.0396536	-.1225689	1.975698	.0212566
L4.	-.1432241	.1663532	.1788722*	2.037315	.0223188
L5.	-.2045923	-.0171241	-.0667921	-.3891836	-.0562455
L6.	-.295297	-.1107141	-.34559*	-.8601076	-.018354
L7.	-.1619422	.0091234	.1072523	-.3059276	.0351207
L8.	-.2562867	-.1278279	.0085028	-2.291851	-.129256*
S&P500					
L1.	.0246406	-.0190752	.0071605	.1936375	.0192795*
L2.	.02906	.000242	-.0102687	.1465134	.0003804
L3.	.0373086	.0257054*	-.0120183	.1418434	-.0036019
L4.	.0262813	-.0058659	.0063339	.1401752	-.0118585
L5.	.0368435	.0351408*	.0135253	.2322039	.0042347
L6.	-.0045338	-.010084	-.0116252	-.1419438	-.0085767
L7.	-.0106612	.0018944	.0015751	-.2425986	-.0040708
L8.	-.0101159	-.025558*	-.0001354	-.0894393	.0039386
Top1wshare					
L1.	1.095482*	.763186*	.4472144*	-8.967993*	-.3109639*
L2.	-.8979628*	-.3695369	.4153457	.4872486	.3588262*
L3.	-.0357444	-.3508289	.1516367	1.779232	.3067464*
L4.	-.3766821	.2624552	-.3876582	-3.827059	.1405501
L5.	-.386601	-.3657891	.3021919	-2.807259	-.1394281
L6.	.7091305	.4938032	.3119851	4.806128	.1830008
L7.	-.32074	-.0606765	-.0209884	4.89681	.0865745
L8.	.0840229	.2755917	-.0433417	3.122961	.1297401
_cons	.0019183	.0045759*	.0000806	.0684544*	.0021012*

* $p < 0.05$